The Active Direct Torque Control of an Induction Motor based on an Artificial Neural Network

Inas Jabbar Mohammed[1*]

Abstract

In this paper, a method is developed to control the induction motor IM using direct torque control (DTC), by means of artificial neural networks (ANN), in order to reach the optimum performance .And then using the MRAS technique, the desired and efficient control of the rotor speed could be estimated and achieved. The design uses the individual training technique with the fixed weight and the controlled models to avoid the difficult DTC calculation. A specific comparison analysis was conducted between both the control for direct torque neural networks (DTNNC) and conventional direct torque control (CDTC) applied to select voltage vector switching. The chassis was designed by Matlab / Simul for DTC.

Key Words: Direct Torque Control (DTC), Induction Motor (IM), Direct Torque Neural Networks Control (DTNNC), Conventional Direct Torque Control (CDTC).

DOI Number: 10.14704/nq.2022.20.4.NQ22333 **NeuroQuantology 2022; 20(4):522-530**

Introduction

Due to their low cost, ease of maintenance, high reliability and ease of provision of their maintenance equipment, the most common engines in industrial applications are induction engines [1].

Electric motors for high performance need decoupled torque and control of flow. By using power by direct torque control in a dynamic way, this happens. Direct torque control (DTC) of an inverter pulse rate motor has gained a lot of attention in recent years. The basic configuration of the induction motor which controls direct torque. Through the diagram shown in Fig.1 as a conventional scheme, the difference between the reference torque T_{ref} and the measured torque rating t_{elm} and there is a line between the two as input for a three-level hindrance comparison, the error between the size of the stator reference flux vector ψ_{Sref} and the size of the stator reference flux vector ψ_S are the vectors Two-level hindrance comparison Figure 1, ST indicates the switching table and MM is the model of inductance. [2-3]. Often this traditional method has several disadvantages

- Variable transfer frequency;
- Present and torque distortions caused by sectorial shifts;
- Starting and low-issues with speed operation;
- High sampling frequency specifications for hysteresis comparators for digital implementation.

In view of the problems listed above and with the purpose of avoiding torque waving and improving the performance of the conventional DTC system, the new method is proposed.

Corresponding author: Inas Jabbar Mohammed
Address: [1*]Electrical power Technologies, Babylon Technical Institute, Al-furat Al-Awsat Technical University, Iraq.
[1*]E-mail: inb.ens4@atu.edu.iq

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.
Received: 24 February 2022 **Accepted:** 30 March 2022

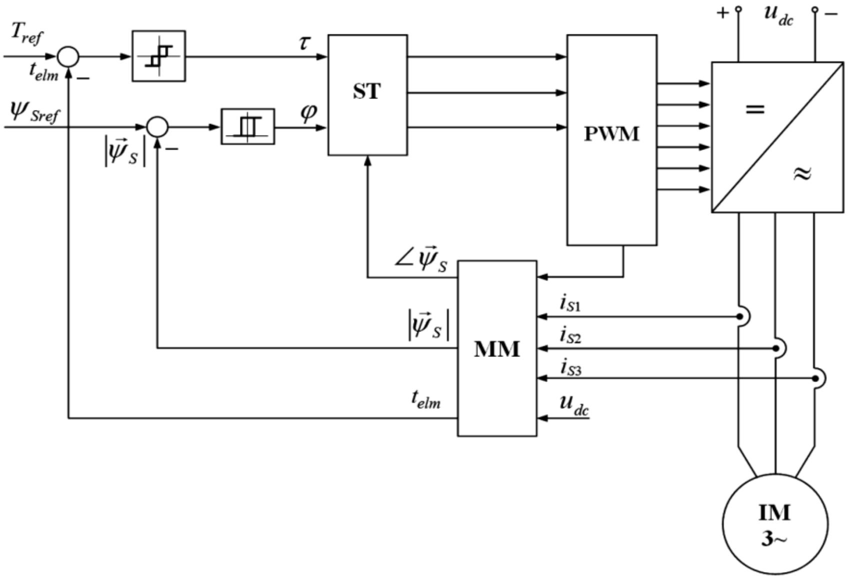


Fig. 1. The conventional scheme for DTC

Table 1 shows the proposed method instead of the traditional method, as the new method includes replacing the Look-up table of switching state selector with a method in which the Auxiliary Artificial Neural Networks controller uses ANN and the use of neural PID instead of the traditional method. In addition, the rotational speed was evaluated by (MRAS) technology.

Table I. Table in the Traditional Method for DTC Switching Table

Section		1	2	3	4	5	6
Φ= 1	τ=1	$\vec{u}_2$	$\vec{u}_3$	$\vec{u}_4$	$\vec{u}_5$	$\vec{u}_6$	$\vec{u}_1$
	τ=0	$\vec{u}_7$	$\vec{u}_0$	$\vec{u}_7$	$\vec{u}_0$	$\vec{u}_7$	$\vec{u}_0$
	τ= -1	$\vec{u}_6$	$\vec{u}_1$	$\vec{u}_2$	$\vec{u}_3$	$\vec{u}_4$	$\vec{u}_5$
Φ= 0	τ=1	$\vec{u}_3$	$\vec{u}_4$	$\vec{u}_5$	$\vec{u}_6$	$\vec{u}_1$	$\vec{u}_2$
	τ=0	$\vec{u}_0$	$\vec{u}_7$	$\vec{u}_0$	$\vec{u}_7$	$\vec{u}_0$	$\vec{u}_7$
	τ= -1	$\vec{u}_5$	$\vec{u}_6$	$\vec{u}_1$	$\vec{u}_2$	$\vec{u}_3$	$\vec{u}_4$

Induction Motor Mathematical Model

There is a complex model for the induction motor that can be derived using the method of transforming three-phase quantities into two direct phases and quadratic quantities. In a static frame of reference such as this, the mathematical model can be given in compressed form. [4-5]:

$$\begin{pmatrix} v_{ds} \\ v_{qs} \\ v_{dr} \\ v_{qr} \end{pmatrix} = \begin{pmatrix} R_s + L_s p & 0 & L_m p & 0 \\ 0 & R_s + L_s p & 0 & L_m p \\ L_m p & \omega_r L_m & R_r + L_r p & \omega_r L_r \\ -\omega_r L_m & L_m p & -\omega_r L & R_r + L_r p \end{pmatrix} \times \begin{pmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{pmatrix} \quad (1)$$

$$\Psi_{ds} = L_s i_{ds} + L_r i_{dr}\,, \Psi_{qs} = L_s i_{qs} + L_r i_{qr} \quad (2)$$

$$\Psi_{dr} = L_r i_{dr} + L_s i_{ds}\,, \Psi_{qr} = L_r i_{qr} + L_s i_{qs} \quad (3)$$

Where V_{ds}, V_{qs}, i_{ds}, i_{qs}, R_s, L_s, R_r, L_r, L_m, Ψ_{ds}, Ψ_{qs}, Ψ_{dr}, Ψ_{qr} and θ_r, the d-q axes are voltages and currents, stator resistance, stator inductance, rotor resistance, rotor inductance, stator and rotor winding mutual inductance, stator flux connections, rotor flux connections, and rotor position, respectively..

The electromagnetic torque obtained from contacts and currents of machine flux is as:

$$T_e = \frac{3}{2}\frac{P}{2} L_m \left(i_{qs}\Psi_{dr} - i_{ds}\Psi_{qr}\right) \quad (4)$$

Where T_e, P, Ψ_{dr}, Ψ_{qr} is the electromagnetic torque, number of poles, rotor d-q axes fluxes respectively.

In a stationary reference frame, the electromagnetic torque equation can also be obtained as a

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{\sigma L_r L_s} |\Psi_r||\Psi_s| \sin\theta_e \quad (5)$$

Where θ_e the angle between the space vectors of the stator and rotor flux relation is e, as shown in Fig.1.

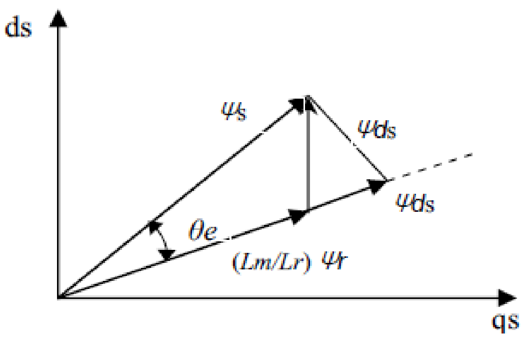


Fig. 2. Space vectors for stator and rotor flux-linkage

Where

$$\sigma = Leakage\ coefficient\ 1 - \left(\frac{L_m^2}{L_s L_r}\right)$$

The stator flux relation, voltage and torque equations can be obtained as fallows in the d-q axis stationary reference frame.

$$v_{ds} = R_s i_{ds} + p\Psi_{ds} \quad (6)$$
$$v_{qs} = R_s i_{qs} + p\Psi_{qs} \quad (7)$$
$$\Psi_{ds} = \int (v_{ds} - R_s i_{ds})\, dt \quad (8)$$
$$\Psi_{qs} = \int \left(v_{qs} - R_s i_{qs}\right) dt \quad (9)$$
$$\Psi_s = \sqrt{\Psi_{ds}^2 + \Psi_{qs}^2} \quad (10)$$
$$\theta_e = \tan^{-1}\left(\frac{\Psi_{qs}}{\Psi_{ds}}\right) \quad (11)$$

Equation 5 shows that the torque of a motor can be modified by changing the rotor flow vectors or the stator. The squirrel cage rotor induction machine has a very high time constant through comparison with the connected stator flux. The rotor flux correlation changes slowly. This flow did not change over a short transient period. Thus, by turning the stator flux in the desired direction, which is determined by the torque order, rapid changes in electromagnetic torque can be induced. On the other hand, by applying suitable stator voltage phases, the stator flux can be accelerated or slowed instantly. Reasonable voltage vectors may be controlled, depending on the stator flux location, to control both flux and torque [13].

The Artificial Neural Networks Concept

A dense interconnection of computing nodes is used by artificial neural networks to approximate nonlinear functions. Each node constitutes a neuron and multiplies its input signals by constant weights, sums up the results and maps the total to a g-function of nonlinear activation; the result is then translated to its output. An ANN forward feed is organized into layers: an input layer, one or more hidden layers, and a layer of output. A MLP is comprised of an input Layers, some secret layers, a few hidden layers [6], [11].

The neuron structure is shown in Figure 2 and the neuron's mathematical model is given by

$$y = \varphi\left(\sum_{i=1}^{N} \omega_i x_i - b\right)$$

Where, $x_i=(x_1, x_2, x_3 \dots x_n)$ are inputs from the neurons of the previous layer $\omega_i=(\omega_1,\omega_2,\dots\dots,\omega_n)$ are the corresponding weights, and 'b' is the neuron bias. The output is given via a logarithmic sigmoidal activation function.

$$y = \frac{1}{1 + e^{\left[\sum_{i=1}^{N} \omega_i x_i - b\right]}}$$

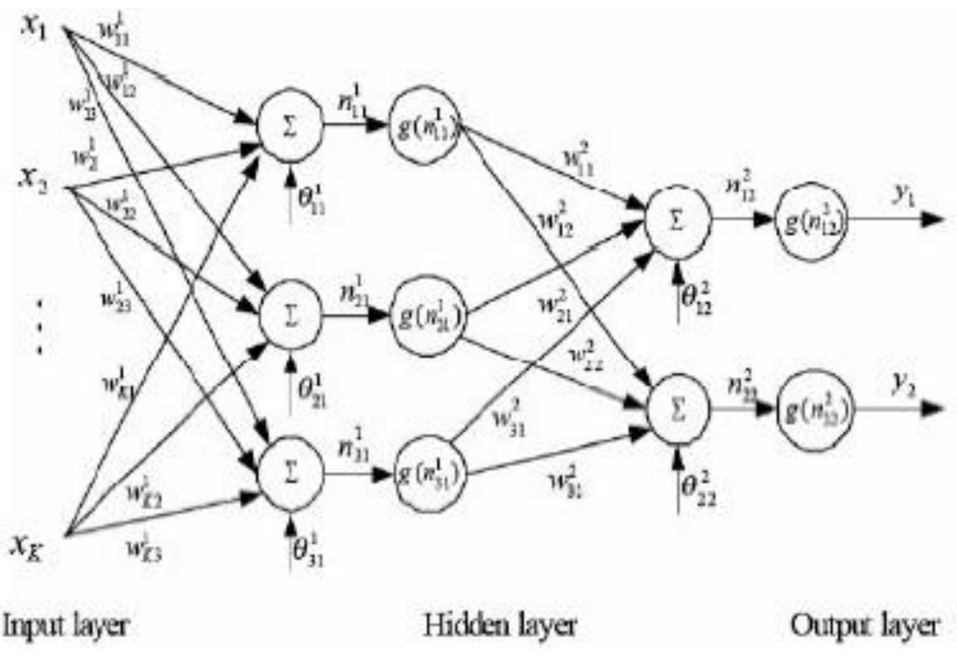


Fig. 3. Neuron Structure

A feed forward neural network has layers: an input layer, one or more hidden layers, and a layer of output. No calculation is carried out in the input layer and the signals are directly supplied from the input layer to the first hidden layer. For hidden and output neurons, there is usually a sigmoidal activation mechanism

DTC Dependent on Neural Network

A neural network is a device like human brain with properties of learning capacity and generalization. It takes a lot of preparation to grasp the model of the farm. This network's basic property is that it can approximate complex nonlinear functions [6]. The neural network is used as a sector selector in the direct torque control scheme, as shown in Figure 3. Torque and flux errors are given to the neural network controller as inputs along with the flux location information in this control strategy [7], [8].

The Artificial Neural Network (ANN) offers the following advantages over other conventional DTC schemes for induction engines.

i. Reduction of Controller Complexity;
ii. Reduction of the effects of changes in motor parameters, in particular in the calculation of stator-flux;
iii. Improving the time response of the controller, i.e., the ANN controller uses only parallel sum processing, constant gain products, and a collection of well-known non-linear functions to minimize computation time.
iv. ANN's are fault tolerant and can derive valuable knowledge from noisy signals to improve drive robustness.

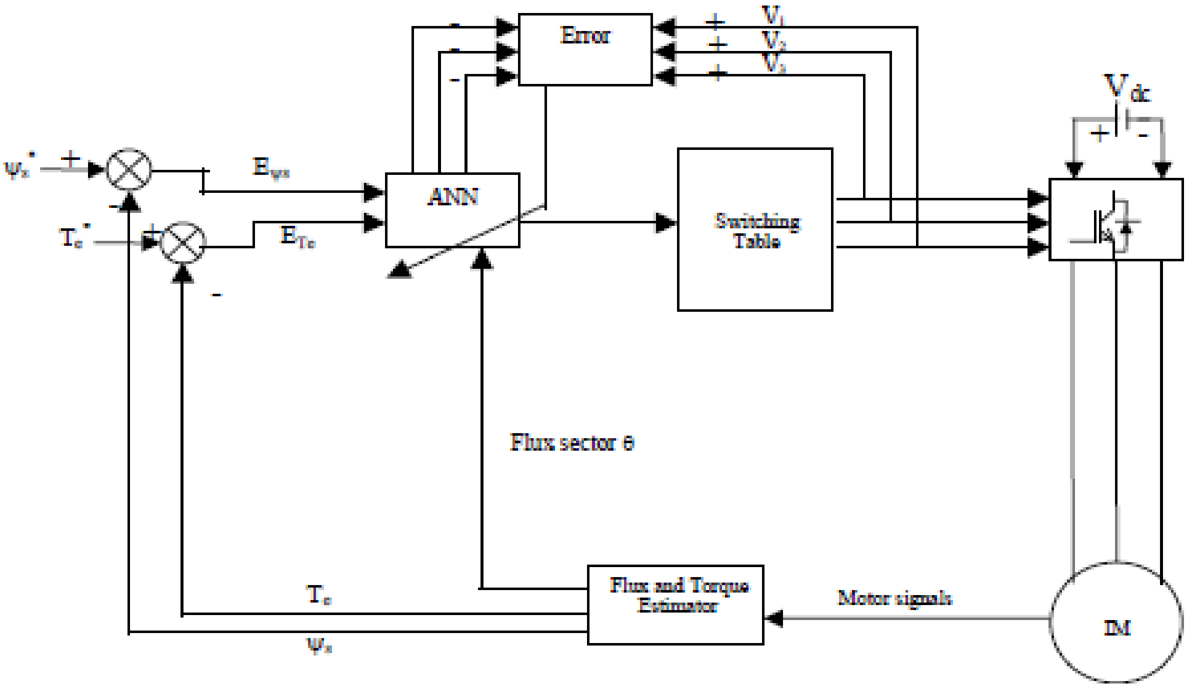


Fig. 4. DTC Schematic with Neural-Network Controller

Algorithms of learning in Neural Networks

Back-propagation [16] is the most popular supervised learning algorithm, which consists of a forward and a backward action. The free parameters of the network are set in the forward phase and the input signals are propagated from the first layer to the last layer all over the network. We calculate a mean square error in the forward step.

$$E(k) = \frac{1}{N}\sum_{i=1}^{N}(d_i(k) - y_i(k))^2 \qquad (12)$$

Where d_i is the desired response, y_i is the actual output produced by the network in response to the x_i input, k is the number of iterations, and N is the number of training data for input-output. The second step in the backward process, the error signal E(k) is propagated in the backward direction across the network of Figure 11 in order to make changes to the free Network parameters to decrease error E(k) in a statistical sense [9]. Therefore, the weights associated with the network output layer are modified using the following formula. [10]:

$$w_{ji}(k+1) = w_{ji}(k) - \eta\frac{\partial E(k)}{\partial w_{ji}(k)} \qquad (13)$$

Where w_{ji} is the weight connecting the output layer's η neuron to the previous layer's η neuron, the constant learning rate is w_{ji}. Large values can speed up ANN learning and therefore faster convergence, but may cause network output oscillations, while low values will cause slow convergence. Therefore, in order to prevent uncertainty, the value of η must be carefully selected.

eISSN 1303-5150

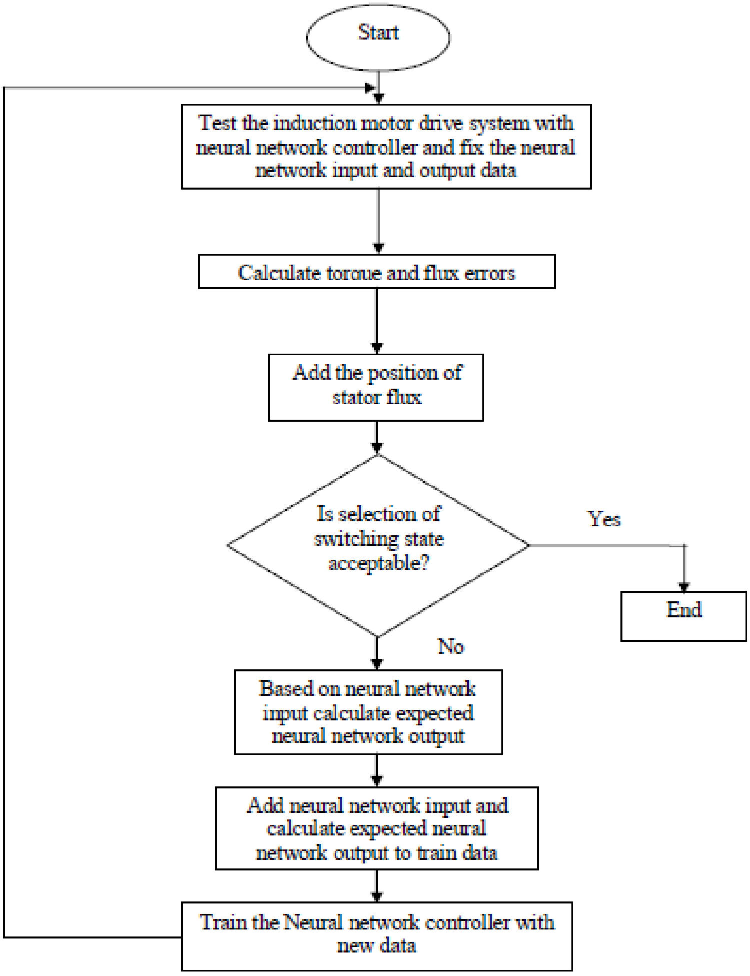


Fig. 5. Flowchart for training back propagation networks

As shown in equation (14), we change the equation formula (13) to ensure rapid convergence, where a positive constant is called the momentum constant.

$$w_{ji}(k+1) = w_{ji}(k) - \eta \frac{\partial E(k)}{\partial w_{ji}(k)} + \alpha \Delta w_{ji}(k) \quad (14)$$

The concrete back propagation training method is illustrated in the flowchart in Figure 5. Once the ANN is properly trained, the validity of the model using data that is different from the training set should be appropriately tested to determine it.

Speed Estimation with MRAS

The fundamental principle of MRAS is the existence of a reference model that specifies the desired states and an adaptive (adjustable) model that produces the states' approximate values. An adaptation mechanism is fed to the error between these states to produce an approximate rotor speed value that is used to change the adaptive model. This process continues until there is a tendency of error between two outputs to zero [2], [14],[15]. It is possible to write simple equations of rotor flux based-MRAS as:

$$\Psi_r^* = \frac{L_r}{L_m}\{V_s - R_s i_s - \sigma L_s i_s\} \quad (15)$$

$$\sigma = 1 - \frac{L_m^2}{L_s L_r} \quad (16)$$

$$\Psi_r = \left(-\frac{1}{T_r} + j\omega_r\right)\Psi_r + \frac{L_m}{L_m} i_s \quad (17)$$

$$T_r = \frac{L_r}{R_r} \quad (18)$$

The reference model (4) is based on stator equations and is thus independent of engine speed, while the adaptive model (6) is velocity-dependent since it is derived from the stationary reference frame rotor equation. The adaptation mechanism compares the two models and an integrated proportional regulator estimates the speed of rotation. By using the principle of Lyapounov stability, we can create a method to adapt the mechanical velocity from the condition of the asymptotic convergence of the asymptotic convergence.

It is possible to write the speed-tuning signal and the estimated speed expressions as [2]:

$$\varepsilon_\omega = I_m(\Psi_r \Psi_r^*) = \Psi_{rq}\Psi_{rd} - \Psi_{rd}\Psi_{rq} \quad (19)$$

$$\omega_r = \left\{k_p + \frac{k_i}{s}\right\}\varepsilon_\omega \quad (20)$$

The conventional MRAS speed observer is shown in Figure 6. [16].

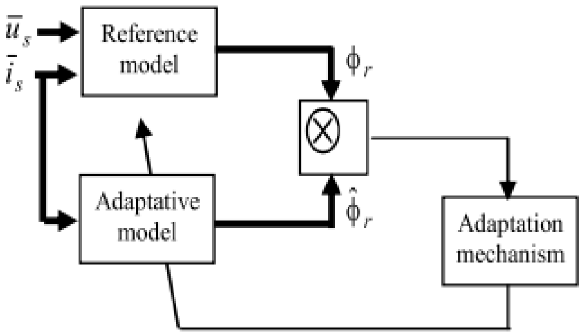


Figure 6. Conventional observer of MRAS speed

Figure 7 displays the proposed system. With an MRAS speed observer, an artificial neural network aided controller is used, so the speed sensor has been omitted and the value of velocity is derived from measurements of electrical signals.

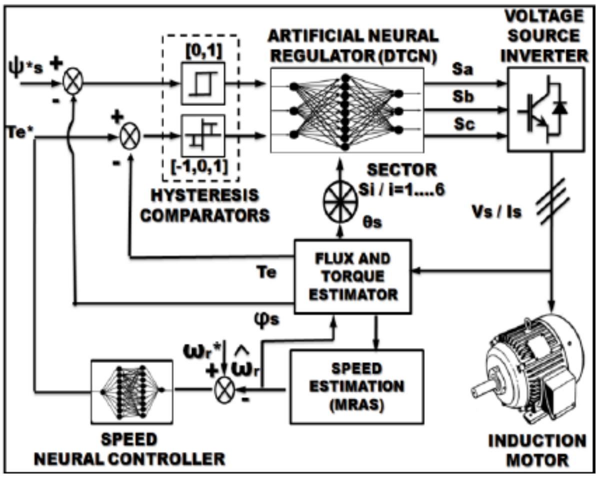
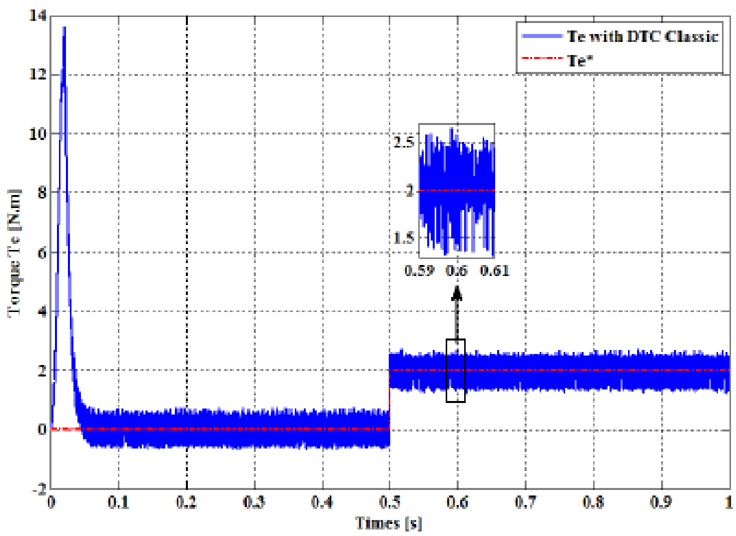


Figure 7. Scheme of proposed neural DTC with estimator of MRAS



(a)

Results of Simulation

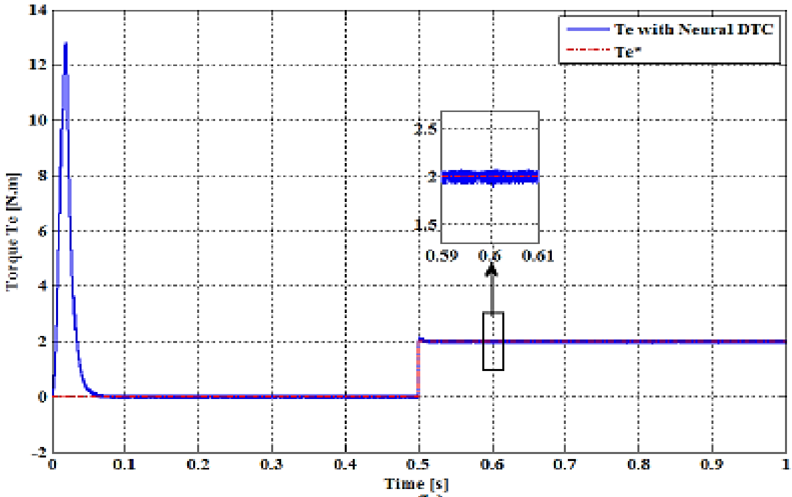
A number of simulations were performed using Matlab / Simulink to analyze the device and compare the performance of the proposed PID controller. Classic DTC and neural DTC were compared using neural PID with MRAS estimation. The PWM inverter for the stator side is operated. Both controllers are checked and compared in the running mod comparison tracking. The references to torque, flux and rotor velocity used in this simulation are *2 N. M* (applied at T_1= *0.5S*, *1Wb* and *148 rad/S.* IM parameters are listed in Table 2.

Table 2. Induction Motor Parameters

Parameters	Values
Number of pairs of poles P	2
Rated power P_n	*1.5KW*
Rated frequency f_n	*50HZ*
Rated speed W_n	142*rpm*
Rated current In	6,4/ 3,7*A*
Rated voltage Vn	220\380
Stator resistance R_s	1.95 Ω
Rotor resistance R_r	1.66 Ω
Stator inductance L_s	244mH
Rotor inductance L_r	243mH
Mutual inductance L_m	369mH
Moment of inertia J	0.025 Kg/m
Viscous friction coefficient f	0,0114. Kg/m²\S

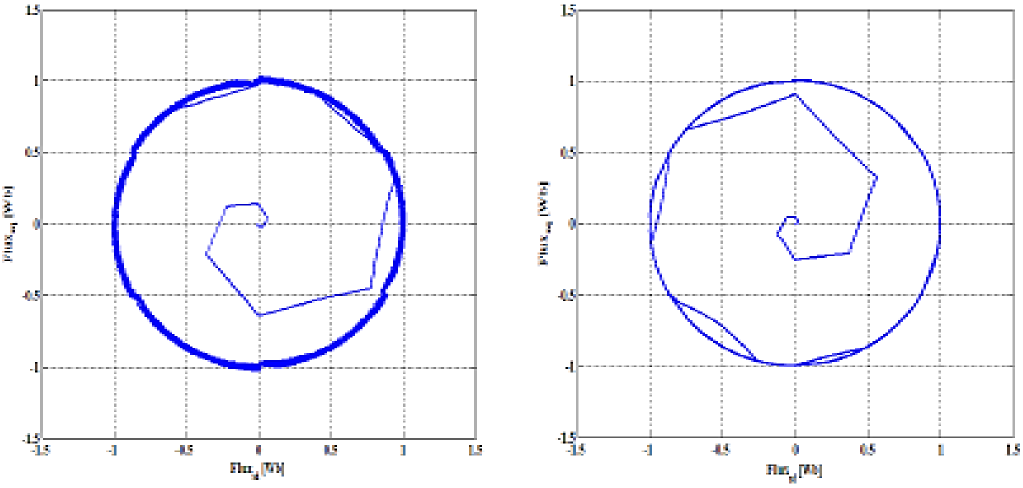
Figures 8 and 9 present the simulation results of the electromagnetic torque and the evolution of the end of the stator vector flux using the conventional DTC (a) and neural network DTC (b).

eISSN 1303-5150



(b)

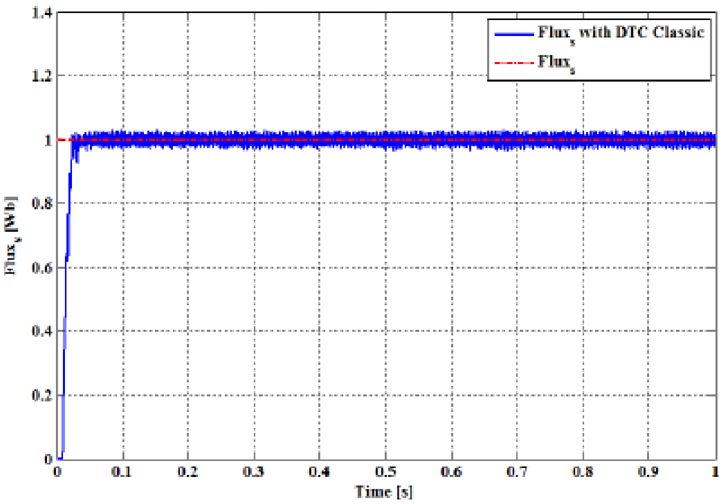
Figure 8. Electromagnetic torques for conventional DTC classic (a) and neural network DTC (b)



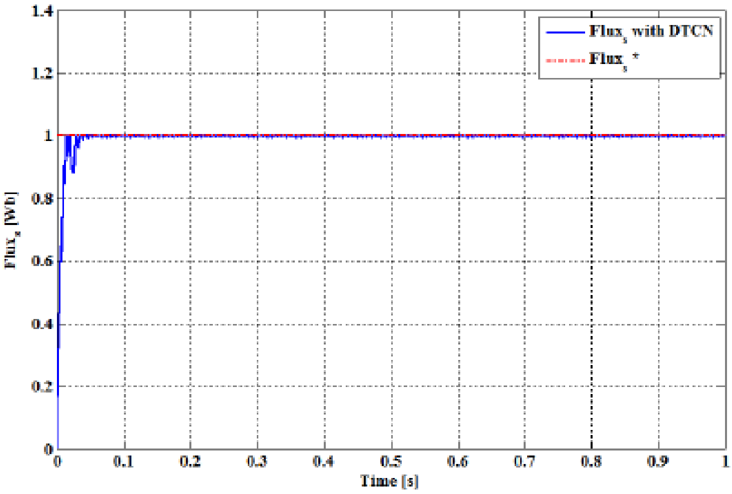
(a) (b)

Figure 9. Comparison of the evolution of the end of the stator vector flux for the DTC Classic (a) and the neural DTC (b)

Figures 10 and 11 present the simulation results of the module of stator flux and the rotor speed using the conventional DTC (a) and neural network DTC (b).



(a)



(b)

Figure 10. Module of stator flux for conventional DTC (a) and neural network DTC (b)

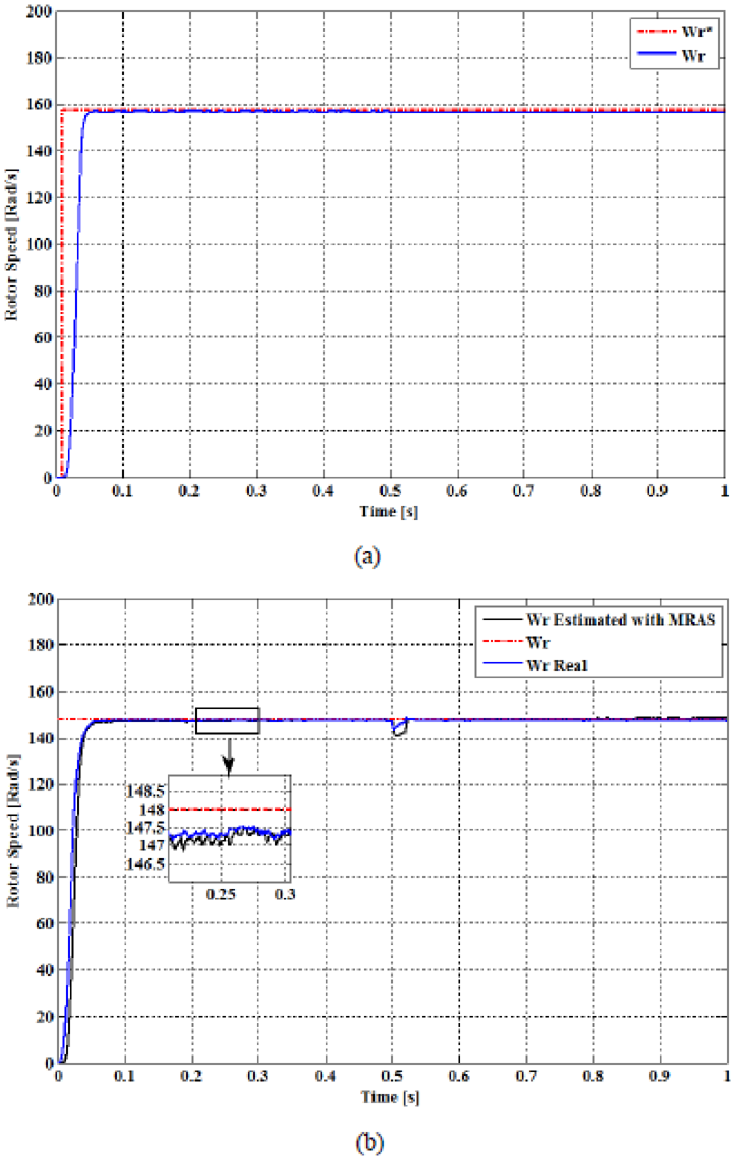


Figure 11. Rotor speed for conventional DTC PID regulator (a) and neural network DTC PID with MRAS estimation (b).

Fig. 10 is a comparison of the torque response with artificial neural networks for the standard DTC approach and the DTC approach. From the answer, we can note that the torque at traditional DTC is significantly more oscillated than with artificial neural networks in the case of the DTC system. The stator flux vector trajectory, which is almost circular, is defined in Fig 11. It can be seen in this figure that the better response is provided by the neural network controller. The response of the stator flux module is exactly followed by its relation in Fig 12 and there is almost no ripple for DTC based on the neural network. The angular velocities are expressed by Fig 13. We can see that the two approaches (conventional DTC and DTC with ANN) do not have a major difference.

Conclusion

In this paper, direct induction motor torque control based on artificial neural networks has been introduced, with speed estimation and regulation using MRAS and PID neural network regulator. The proposed control strategy provides the following advantages: reduction of flux and torque ripples; and operation of the system without a speed sensor. The results show that the settling time is substantially reduced with neural network DTC, peak overshoot values are limited and oscillations are damped.

References

Rajesh Kumar' Artificial neural network based direct torque control of induction motor drives' (ICTES 2007).

Dubravko Krušelj, Methods for Direct Torque Control of Induction Machines, International Conference on Electrical Drives and Power Electronics (EDPE) Dubrovnik, 04-06 Oct. 2017.

S Allirani and V Jagannathan "High Performance Direct Torque Control of Induction Motor Drives Using Space Vector Modulation''IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 6, November 2010.

Emmanuel, Jean- LOUIS 'Modeling and control of induction motors' Int. J. Appl. Math. Comput. *Sci*., 2001, Vol.11, No.1, 105-129.

C.M. Ong, Dynamic Simulation of Electric Machinery Using Matlab/Simulink, Prentice Hall, 1997.

Xiufeng Wang, M. Elbuluk, Neural network control of induction machines using genetic algorithm training, ieeexplore. ieee., orgIAS'96. Conference Record of the 1996.

Bambang Purwahyudi, Neural network technique for direct torque control of induction motor used in electrically driven marine propeller, international journal of academic research, Vol. 3. No. 5. September, 2011.

M.N. Cirstea, A. Dinu, J.G. Khor, M. McCormick, Neural and Fuzzy Logic Control of Drives and Power Systems, Newnes, An imprint of Elsevier Science First published 2002. 412 pages.

S. Haykin, "Neural Network – A comprehensive Foundation", Prentice Hall 1999. 897 pages.

Alessandro Goedtel, Ivan Nunes Da Silva, P. J. A. Serni, Neural Approach for Induction Motor Load Torque Identification in Industrial Applications, IEEE Conference on Control Technology and Applications (CCTA)2007.

Alberico Menozzi, Mo-yuen Chow, "A design methodology for an intelligent controller using fuzzy logic and Artificial Neural Networks,1993 IEEE, P-408-413.

Ali Abdullah, Mohammed Ali, Direct torque control of IM using PID controller, International Journal of Electrical and Computer Engineering (IJECE) Vol. 10, No. 1, February 2020, pp. 617~625.

Takahashi I, Noguchi T. A new quick-response and high efficiency control strategy of an induction motor, IEEE trans. Vol IA-22, no 5. 1986.

F. haghgoeian, M.A. ouhrouchie & J.S.thongam, Speed Estimation Using Neural Network in Vector Controlled Induction Motor Drive, WSEAS Int. Conf. on dynamical systems and control, Venice, Italy, November 2-4, 2005 (pp592-597).

S.Meziane, R.Toufouti, H.Benalla, MRAS based Speed Control of sensorless Induction Motor Drives, ICGST-ACSE Journal, Volume 7, Issue 1, May 2007.

Idriss Benlaloui, Saıd Drid, Implementation of a New MRAS Speed Sensorless Vector Control of Induction Machine, IEEE transaction of energy conversion, vol. 30, no. 2, june2015.